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A SEM-neural network approach for predicting antecedents of m-commerce acceptance

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ABSTRACT

Higher penetration of powerful mobile devices – especially smartphones – and high-speed mobile internet access are leading to better offer and higher levels of usage of these devices in commercial activities, especially among young generations. The purpose of this paper is to determine the key factors that influence consumers' adoption of mobile commerce. The extended model incorporates basic TAM predictors, such as perceived usefulness and perceived ease of use, but also several external variables, such as trust, mobility, customization and customer involvement. Data was collected from 224 m-commerce consumers. First, structural equation modeling (SEM) was used to determine which variables had significant influence on m-commerce adoption. In a second phase, the neural network model was used to rank the relative influence of significant predictors obtained from SEM. The results showed that customization and customer involvement are the strongest antecedents of the intention to use m-commerce. The study results will be useful for m-commerce providers in formulating optimal marketing strategies to attract new consumers.

1. Introduction

The rapid advancements in mobile technologies have stimulated higher penetration of mobile devices and the growth of its use in various areas of our lives (Dai & Palvia, 2009). The number of mobile phone subscribers is well above the number of fixed-line Internet users. Mobile penetration, i.e. the number of mobile subscriptions per 100 inhabitants, on global level stands at 96.4% (International Telecommunication Union, 2014), but it is much higher in developed countries (125.8%), where it is reaching saturation. Modern mobile devices, especially smartphones and tablets, are no longer used only for voice communication, but as complex communication devices which enable wireless Internet access, high-speed data transfer and numerous services, including rich multimedia and financial applications. For example, in developing countries, mobile phones are often the first-access device to the Internet (Nielsen, 2014).

Mobile commerce is defined as the buying and selling of goods and services through mobile devices via wireless networks (Chong, 2013a) and it is one of the fastest growing businesses today. Although often considered as an extension of e-commerce (Chong, Chan, & Ooi, 2012), m-commerce has some advantages over its predecessor, since users may conduct transactions on the Internet at any time, from anywhere. Also, it offers completely new possibilities, like location-based services. As eMarketer (2014) predicts, U.S. retail m-commerce sales (sales of digital goods, excluding sales of travel services and event and movie tickets) in 2018 will reach $132 billion, which is double of the estimates for 2014.

Despite the strong potential of mobile commerce, the actual level of such activities remains low, especially in developing countries (Bhatti, 2007; Chong, 2013c). Therefore, identification of the factors influencing the consumers' intention to use mobile commerce applications is very important, as it would help m-commerce providers to create appropriate marketing strategies, leading to higher m-commerce adoption rates (Chan and Chong, 2012; Wei, Marthandan, Chong, Ooi, & Arumugam, 2009; Wu and Wang, 2005).

The present study fills the existing research gap by developing a new research model used for the prediction of consumers' behavior and examination of key elements that influence the decision to use m-commerce. The originality of the model is based on the fact that it consists not only of well-known predictors of new technology adoption, like perceived usefulness, perceived ease of use and trust, but also includes variables like mobility, customization and customer involvement, whose influence on m-commerce adoption is examined in a very limited number of studies. In line with that, the main objectives of the study are to determine the most significant factors influencing m-commerce adoption and their relative

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importance. One of the main drawbacks of conventional statistical techniques used for the prediction of consumers' behavior is that they usually examine only linear relations among variables. In order to overcome this problem, relative importance of significant variables will be determined using neural networks, capable to model complex non-linear relationships.

The paper is structured as follows: Section 2 introduces the literature review of similar studies on m-commerce adoption. Section 3 outlines proposed hypotheses and research model. Section 4 details the used methodology, while Section 5 presents data analysis and the research results. In Section 6, we discuss various implications of the obtained results. Finally, in Section 7, we explain the main limitations of our study and potential steps for further research.

2. Literature review

The analysis of consumer behavior and determinants influencing their decision to adopt new technology, like m-commerce, is usually performed using some of the well-known traditional theories on technology adoption, such as the technology acceptance model (TAM), diffusion of innovation (DOI), task-technology fit (TTF), and unified theory of acceptance and use of technology (UTAUT). TAM, as one of the most common models, was proposed by Davis (1989) and it is an adaptation of the theory of reasoned action (Fishbein & Ajzen, 1975). Although it is well-established as a powerful and robust model for predicting user acceptance (Zhang, Zhu, & Liu, 2012), it is often considered incomplete (Brown & Venkatesh, 2005; Davis, 1989; Lu, Yao, & Yu, 2005). In order to better explain and predict consumer behavior, several studies have suggested that it should be extended with additional constructs (Chong et al., 2012; Wei et al., 2009; Wu & Wang, 2005).

Unlike the traditional TAM, where two of its crucial beliefs – perceived usefulness and perceived ease of use – are used as mediators between external variables and outputs (attitude towards use and/or behavioral intention), this study analyzes the direct effect of external factors on behavioral intention. Several previous studies support this attitude. For example, Wei et al. (2009), while analyzing the drivers of m-commerce adoption in Malaysia, used two TAM predictors (perceived usefulness and perceived ease of use) and added direct influence of new variables – social influence, trust and perceived cost – on consumer intention to use m-commerce. They reported that the most important adoption factors were perceived usefulness and trust. Wu and Wang (2005) added perceived risk, cost and compatibility and found compatibility and perceived usefulness as the most significant antecedents.

In the study of mobile ticketing services adoption, Mallat, Rossi, Tuunainen, and Oorni, 2008 added nine more predictors and found prior experience, compatibility and social influence as the most significant ones. Zarmpou et al. (2012) analyzed the acceptance of mobile services, and extended the model with the following variables: functionality, trust, innovativeness and relationship drivers. The results showed that the most significant predictors were innovativeness and perceived usefulness, while no significant direct influences of perceived ease of use and trust on behavioral intention were found. Tan, Ooi, Chong, and Hew, 2014 studied the determinants of NFC-based mobile credit card adoption by extending TAM constructs with new variables: social influence, personal innovativeness, perceived risk and cost, and found that personal innovativeness and perceived ease of use were the strongest predictors.

Chong et al. (2012) extended the model with trust, cost, social influence, variety of services and trialability as additional direct antecedents of intention to adopt m-commerce. They reported that the most significant factors influencing Malaysian consumers were variety of services, trust and social influence, while in the case of Chinese consumers, it were trust, social influence and cost. In the cross-cultural study of m-commerce acceptance, Dai and Palvia (2009) added eight more variables, and found that perceived usefulness and subjective norm had the most important influence on intention to use m-commerce in China, compared to perceived enjoyment and compatibility in the United States. Chong (2013b) extended basic TAM beliefs with perceived enjoyment, trust, cost, network influence and variety of services, and reported that the most influential on m-commerce adoption were network influence and trust.

In meta-analysis of numerous studies, Zhang et al. (2012) analyzed the influence of the ten most frequent predictors on behavioral intention to adopt m-commerce and reported perceived enjoyment and subjective norm as the most significant. Chemingui and Iallouna (2013) also found perceived enjoyment as the most significant predictor of behavioral intention to adopt mobile financial services.

3. Development of hypotheses

Behavioral intention is often found as the best predictor of behavior, i.e. actual use of new technology (Zhang et al., 2012), and represents a central concept of both TAM (Davis, 1989) and UTAUT (Venkatesh, Morris, Davis, & Davis, 2003a) models. In the m-commerce context, behavioral intention may be defined as a consumer's subjective probability that he/she will use mobile commerce (Zarmpou, Saprikis, Markos, & Vlachopoulou, 2012). Since m-commerce is still in its early stage of implementation, especially in developing counties, we decided, like in similar studies (Chong et al., 2012; Dai and Palvia, 2009; Wei et al., 2009; Zarmpou et al., 2012), to examine not the actual use but the behavioral intention to adopt m-commerce.

3.1. Perceived usefulness

Perceived usefulness, as one of the original TAM variables, is constantly found to have significant influence on new technology acceptance. It is usually considered as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989; p 320). In the m-commerce context, Wei et al. (2009) defined it as the extent to which a consumer believes that, while using m-commerce, his or her job performance and daily activities will be improved. Compared to other important TAM construct – perceived ease of use – perceived usefulness usually has a stronger influence on new technology adoption (Davis, 1989). Chong (2013b) stressed the opinion that consumers will accept some new technology such as m-commerce only if they find it to be more useful than its alternatives, such as e-commerce.

Perceived usefulness was examined as a predictor of new technology acceptance in various areas, such as m-payment (Kim, Mirusmonov, & Lee, 2010; Liebana-Cabanillas, Sanchez-Fernandez, & Munoz-Leiva, 2014a; Schiertz, Schilke, & Wirtz, 2010; Shin, 2009), Internet banking (Cheng, Lam, & Yeung, 2006; Chong, Ooi, Lin, & Tan, 2010; Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, 2004), mobile Internet (Kim, Chan, & Gupta, 2007) and m-services (Mallat, Rossi, Tuunainen, & Oorni, 2009; Zarmpou et al., 2012). Wei et al. (2009) found perceived usefulness as the most significant of five examined predictors of intention to use m-commerce in Malaysia. Also, Ko, Kim, and Lee, 2009 reported perceived usefulness as a strong antecedent of intention to adopt mobile shopping in Korea. Liebana-Cabanillas, Sánchez-Fernandez, and Munoz-Leiva, 2014b found that the impact of perceived usefulness on intention to use mobile payment is significantly higher among men than among women, and that usefulness had no statistically significant effect on intention to use among women. Analyzing different m-commerce usage activities, Chong (2013c) and Chan and Chong (2013) found that perceived usefulness had significant influence on content delivery, transaction-based and entertainment activities, while non-significant relationship with location-based services was found. In their cross-cultural study, Dai and Palvia (2009) found perceived usefulness as a significant predictor of intention to use mobile commerce in both China and the United States. The strong, direct effect of perceived usefulness on behavioral intention to use m-commerce has also been confirmed by Chong (2013b), Wu and Wang (2005) and Zhang et al. (2012). However, several studies found no evidence to support this influence (Aldas-Manzano, Ruiz-Mafe, & Sanz-Blas, 2009; Bhatti, 2007; Chong et al., 2012).

Perceived usefulness is one of the most widely studied variables in the adoption of any new technology, including m-commerce. Therefore, we propose the following hypothesis:

H1. Perceived usefulness has significant and positive effect on behavioral intention.

3.2. Perceived ease of use

Perceived ease of use is also one of the original TAM constructs. Based on the original Davis (1989) definition, Vijayasarathy (2004) defined ease of use in the online shopping context as “the extent to which a consumer believes that on-line shopping is free of effort.” Despite high mobile phone penetration, even in developing countries, m-commerce applications remain a novelty for consumers and its diffusion might be slow, particularly among inexperienced users (Chong, 2013b; Schiertz et al., 2010). Therefore, perceived ease of use should be considered as a very important factor of adoption i.e. mobile services must be both easy to learn and easy to use (Kim et al., 2010; Liebana-Cabanillas, Munoz-Leiva, & Sánchez-Fernandez, 2015).

Perceived ease of use has been used as an influential factor in many Internet-based studies in different areas, including e-services (Featherman, Miyazaki, & Sprott, 2010), mobile payment (Kim et al., 2010; Liebana-Cabanillas et al., 2014a; Schiertz et al., 2010; Shin, 2009), Internet banking (Cheng et al., 2006; Chong et al., 2010; Pikkarainen et al., 2004), mobile services (Mallat et al., 2009; Zarmpou et al., 2012) and mobile Internet (Kim et al., 2007). Tan, Ooi, Chong et al. (2014) found perceived ease of use as a strong predictor of the intention to adopt NFC-based mobile credit cards. In the study of different m-commerce usage activities, Chong (2013c) and Chan and Chong (2013) reported perceived ease of use as a significant antecedent of all four activities analyzed: content delivery, transaction-based activities, entertainment and location-based services. Chong (2013a) found that perceived ease of use had a significant influence on continuance intention to use m-commerce. In cross-cultural study of China and USA, Dai and Palvia (2009) found perceived ease of use as a significant antecedent of intention to use mobile commerce among Chinese consumers, but no significant relationship among consumers in the United States. The significant importance of perceived ease of use on behavioral intention to use m-commerce has also been confirmed by Bhatti (2007) and Zhang et al. (2012). However, in their cross-cultural study, Chong et al. (2012) found no significant relationship between perceived ease of use and intention to use m-commerce, among both Chinese and Malaysian consumers. Also, several other studies found no evidence to support this influence (Chong, 2013b; Lu, 2014; Wei et al., 2009; Wu and Wang, 2005; Zarmpou et al., 2012), so there are opposing results of previous studies. Therefore, we propose the following hypothesis:

H2. Perceived ease of use has significant and positive effect on behavioral intention.

3.3. Trust

M-commerce is still in its early development stage and many users are still not familiar with all its aspects and characteristics, which often raises questions of trust, security and privacy issues. Consumer trust is considered as one of the most important factors in commerce, including e-commerce and m-commerce (Min, Ji, & Qu, 2008; Wei et al., 2009) and the lack of trust is one of the main reasons why buyers do not purchase from internet shops (Gefen, Karahanna, & Straub, 2003). Quelich and Klein (2006) stated that trust is “a critical factor in stimulating purchases over the Internet, especially at this early stage of commercial development”.

Trust in the context of m-commerce may be defined as “the extent to which an individual believes that using m-commerce is secure and has no privacy threats” (Wei et al., 2009). Lin and Wang (2006) defined trust as a set of beliefs dealing primarily with the integrity (m-commerce service provider honesty and promise keeping), benevolence (provider caring and motivation to act in consumer’s interest), competence (ability of provider to do what consumer needs) and predictability (provider’s behavioral consistency). Min et al. (2008) discussed that in the case of m-commerce, user acceptance is not only the acceptance of mobile technology but also the acceptance of m-commerce service providers, and elaborated that the users’ trust of m-commerce service providers is even more important.

Lu, Yu, Liu, and Yao (2003) stated that mobile connections, compared to wired Internet, are exposed to higher insecurity levels, and therefore the importance of trust in m-commerce should be relatively higher compared to e-commerce, which is also confirmed by Cho, Kwon, and Lee (2007). Chong et al. (2012) found that both Malaysian and Chinese users are generally concerned about the security and privacy offered by m-commerce, and that trust plays a significant role in m-commerce adoption. Also, Wei et al. (2009) found that trust is one of the most important adoption factors of m-commerce in Malaysia. Significant impact of trust on m-commerce acceptance, direct or indirect, was also found in Chong (2013a), Chong (2013b) and Leong et al. (2013). Shin (2009) found that trust has significant influence on consumer’s intention to use mobile wallet. Liebana-Cabanillas et al. (2014a) confirmed that the impact of trust in m-payment on the attitude toward it is significantly stronger among women, thus increasing their intention to use. Also, Mallat et al. (2008) reported significant influence of trust on intention to use mobile ticketing services. Trust is found as one of the strongest predictors of behavioral intention to mobile banking (Gu, Lee, & Suh, 2009) and internet banking (Akhiaq & Ahmed, 2013; Chong et al., 2010; Kesharwani & Bisht, 2012).

Zhang et al. (2012) found moderate but significant influence of trust on behavioral intention to use m-commerce, in both eastern and western cultures. Morosan (2014) also reported moderate but significant influence of trust on attitude and, indirectly, on intention to adopt mobile phones for purchasing ancillary services in air travel. In their study, Zarmpou et al. (2012) found no direct influence of trust on behavioral intention, but found very strong influence of trust on perceived usefulness (and therefore, indirect influence of trust on behavioral intention) and only marginal impact on perceived ease of use. On the other hand, in some studies trust was not found to be relevant for user intention to adopt m-commerce (Alkhunaizan & Love, 2014) or mobile financial services (Chemingui & Iallouna, 2013; Koenig-Lewis, Palmer, & Moll, 2010).

Since the impact of trust in the m-commerce context is considered to be very important, we propose the following hypothesis:

H3. Trust has significant and positive effect on behavioral intention.

3.4. Mobility

Mobility *per se* is considered as the most significant quality of mobile technology and critical advantage over traditional approaches (Kim et al., 2010). Mobile commerce perfectly fits with the mobile nature of modern lifestyle, providing a means for shopping and service providing in virtually any life situation (Schiertz et al., 2010). The temporal and spatial dimensions of mobility enable consumers to access communication, information and services at any time, from any location (Kim et al., 2010).

While usefulness and mobility are both benefits of technology, the main difference is that usefulness takes the benefits of technology as general, whereas mobility captures only the advantages of mobile technology (Mallat et al., 2009). Schiertz et al. (2010) found significant positive influence of mobility on attitude towards use, intention to use and perceived usefulness of mobile payment services. Kim et al. (2010) reported that mobility was a significant predictor of perceived usefulness, but no significant relationship was found between mobility and perceived ease of use. Mallat et al. (2009) found significant relationship between mobility and use context in predicting intention to use mobile ticketing. Perceived mobility was also found as one of the significant antecedents of perceived usefulness of mobile learning (Huang, Lin, & Chuang, 2007) and 4G LTE mobile services (Park & Kim, 2013).

Mobility is one of the key advantages of mobile technologies and its benefits influence consumer's intention to use m-commerce. Therefore, we propose the following hypothesis:

H4. Mobility has significant and positive effect on behavioral intention.

3.5. Customization

Customization may be viewed as a degree to which the company's offer is well adapted to meet heterogeneous customer needs (Anderson, Fornell, & Rust, 1997). Liao, Li, and Xu (2005) defined customization in m-commerce as "the use of mobile technologies and of user, context, and content information to provide personalized products/services so as to meet the specific needs of the individuals", where individuals are both customers and merchants. Modern mobile devices are designed to accommodate personalization from both user and organizational perspectives, and consumers can personalize many aspects of their interaction with vendors/service providers, like to get only the most relevant offer/content at preferred time or to store all personal and financial details for a more efficient purchasing process (Morosan, 2014).

Yeh and Li (2009) found positive influence of customization, as one of the quality characteristics of the m-commerce provider's website, on customer satisfaction and customer trust towards the m-commerce provider. Choi, Seol, Lee, Cho, and Park (2008) reported customization as one of the two common critical factors to both m-commerce and e-commerce. In his study of adoption of mobile technologies in air travel, Morosan (2014) reported customization as a significant predictor of both perceived usefulness and perceived ease of use. Personalization, which is usually considered as technology-oriented customization (Venkatesh, Ramesh, & Massey, 2003b), was found as an important predictor of brand loyalty and perceived quality in the m-commerce context, i.e. consumers considered more personalized m-services as of higher quality and more often would become loyal to the brand (Wang & Li, 2012).

The advantages of customized offer and personalized content may attract and keep the customers loyal. Therefore, we propose the following hypothesis:

H5. Customization has significant and positive effect on behavioral intention.

3.6. Customer involvement

Communication with customers is an important factor in the successful development of a new product or service. In this way, managers are able to receive a great deal of useful information from consumers that can improve the quality of the new product development (Brown & Eisenhardt, 1995). Customers are in a position to convey to managers their experiences regarding the use of products and services. Managers become more familiar with consumer perception concerning characteristics and benefits of the product (Bettencourt, 1997; Yi and Gong, 2013). Involving consumers in the process of creating a new service can enhance provider's commitment service and improve relations between the two sides.

In a study conducted by Svendsen, Haugland, Grønhaug, and Hammervoll (2011) a positive significant effect of customer involvement on relationship profitability was confirmed. In this context, our study is based on the assumption that a high level of consumer involvement in the process of creating service and consumer feedback can initially enhance customer intention to use m-commerce. This is particularly important when it comes to the

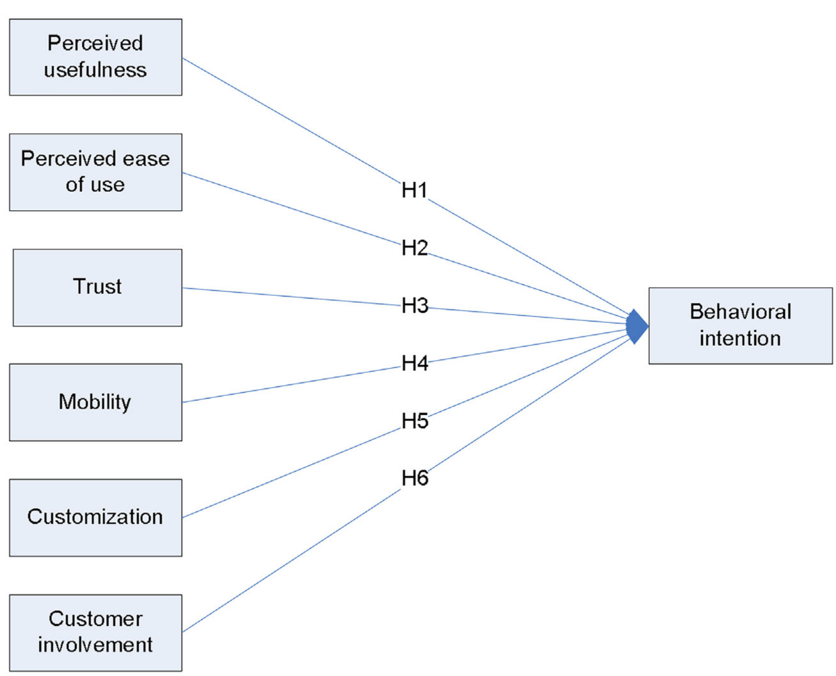

Fig. 1. Research model.

Table 1
Sample structure.

	Number of respondents	%
Gender		
Female	125	55.8
Male	99	44.2
Age		
18–24	59	26.3
25–34	68	30.4
35–44	51	22.8
45 or more	46	20.5
Education level		
Secondary school	101	45.1
Higher school	29	12.9
University	94	42.0

relatively new services, such as m-commerce. Accordingly, we have formulated the following hypothesis:

H6. Customer involvement has significant and positive effect on behavioral intention.

The research model, comprising six predictors of intention to use m-commerce, is shown in Fig. 1.

4. Research methodology

4.1. Sample and data collection

The research was conducted on a sample that included 224 respondents. Respondents are the customers of three mobile operators with offices and branches in the Republic of Serbia. Prior to the distribution of questionnaires, their preliminary testing was conducted in two phases. In the first phase, a focus group was organized which consisted of several university professors and employees of mobile operator companies. The focus group participants discussed the comprehensibility of defined statements in the questionnaire. In this context, some adaptations of initially formulated statements were made so they would be clearer to respondents. In the second phase, pilot testing of the questionnaire was carried out on a small sample of 30 respondents. After completing the questionnaire, each respondent shared his/her impressions on the questionnaire with the researchers and pointed out possible ambiguities. After additional adaptations, the final version of the questionnaire was created.

In accordance with the instructions received from the researchers, the interviewers contacted the respondents on their way out of the shops of mobile operators. Only those customers who have implemented certain commercial activity via mobile phone in the last year could be included in the research. In addition, respondents were offered to give interviewers their phone numbers and to bring questionnaires home to fill them out alone. Three days later, interviewers contacted the respondents in order to take the questionnaire. Upon further review and exclusion of incomplete questionnaires, the researchers have completed a list of 224 valid questionnaires. Demographic structure of the sample is shown in Table 1. It is important to note that the respondents were contacted on three occasions, twice on weekdays (once in the morning and once in the afternoon), and on Saturday. Interviews at various daily intervals of both weekdays and weekends gave the opportunity for the researchers to sample a wider range of users with a larger variety of business and demographic profiles.

4.2. Measurement of variables

The conceptualized research model included six independent and one dependent variable. The model contains a total of 25 statements which were rated by respondents on a seven-point Likert scale (score 1 indicates strong disagreement, while score 7 indicates strong agreement with the statement). In addition, each variable was measured on the basis of three or four statements. Selection of the statements was made based on a review of relevant literature (the full list of items is given in Appendix A).

Table 2
Reliability analysis.

Variables	Cronbach's alpha
Trust	0.927
Usefulness	0.942
Ease of use	0.946
Mobility	0.924
Customization	0.920
Customer involvement	0.743
Behavioral intention	0.918

5. Data analysis and results

5.1. Reliability and validity analysis

Statistical data analysis was carried out in three steps. In the first step, the validity of the conceptualized research model was assessed. The reliability of model variables was determined by considering the value of Cronbach's alpha coefficient. In addition, the convergent and discriminant validity, as well as composite reliability, were tested using confirmative factor analysis. In the second step of the analysis, structural equation modeling (SEM) was applied using maximum likelihood estimation to test hypotheses. In the third step, using neural networks, we have verified the strength of the effect of independent variables on dependent variables whose significance was determined by SEM analysis. Data analysis was conducted in the Statistical Package for Social Sciences (SPSS 20) and AMOS 18.

At the very beginning, using the item to total correlation approach, the degree to which individual statements are correlated with the variables for which measurement they were used was determined. In order to ensure better validity and compliance of the model, one statement that was used for the measurement of customer involvement was excluded. Subsequently, analyzing the value of Cronbach's alpha coefficient, reliability and internal consistency of the statements according to which the latent variables of the model were measured was estimated. The results of the reliability analysis are shown in Table 2. In case of all variables there is an adequate level of reliability that exceeds the threshold of 0.7 (Nunnally, 1978). Specifically, the values of Cronbach's alpha coefficient range between 0.743 and 0.946. Except for the variable customer involvement, in the case of other variables Cronbach's alpha coefficient values are higher than 0.9.

Table 3 shows the intercorrelation matrix, as well as the values of average variance extracted (AVE) and composite reliability (CR) of each structure individually. As can be seen in the table, in the case of all variables the AVE values are higher than the threshold of 0.5. Thereby, convergent validity of the model is supported (Fornell & Larcker, 1981). All confirmatory factor loadings exceeded 0.65, and all were significant at the alpha level of 0.05. Given that the AVE value of each structure is higher than the squared correlation coefficient between the given and other structures, discriminant validity was supported as well. In particular, the values of correlation coefficients between the variables of the model range between 0.36 and 0.76. Finally, it is important to point out that the CR values of all structures exceeded 0.6 (Bagozzi & Yi, 1988).

In order to assess the fit of the proposed model, the values of the corresponding goodness-of-fit indicies were analyzed. The results indicate that the model reasonably fits the data. Value of the ratio $\chi2/\mathrm{df}$ is 2.05 and it is lower than the threshold of 3, recommended

Table 3
Intercorrelation matrix, AVE and CR.

	1.Trust	2.Usefulness	3.Ease of use	4.Mobility	5.Customization	6.Customer involvement	7.Behavioral intention
1	1						
2	0.58	1					
3	0.50	0.40	1				
4	0.47	0.36	0.75	1			
5	0.60	0.58	0.69	0.67	1		
6	0.36	0.45	0.55	0.48	0.67	1	
7	0.58	0.57	0.59	0.55	0.76	0.71	1
AVE	0.76	0.85	0.81	0.76	0.79	0.62	0.75
CR	0.93	0.94	0.95	0.92	0.92	0.76	0.92

Notes: All correlations were significant at 0.05 level.

Table 4
Fit indices in the proposed model.

Fit indicies	Value in the model
χ^2/df	2.05
RFI	0.90
AGFI	0.80
GFI	0.85
NFI	0.91
CFI	0.95
TLI	0.94
IFI	0.95
RMSEA	0.07

Notes: RFI – relative fix index; AGFI – adjusted goodness-of-fit index; GFI – goodness-of-fit index; NFI – normed fit index; CFI – comparative goodness of fit; TLI – Tucker-Lewis Index; IFI – incremental fit index; RMSEA – root mean square error of approximation.

by Carmines and McIver (1981). Adequate values were obtained based on other fit indicies as well (Table 4). The values of AGFI and GFI are 0.80 and 0.85, respectively. In the case of RFI, NFI, CFI, TLI, and IFI indices the values obtained are ≥0.90. The value of the RMSEA index is also within the desirable interval between 0.05 and 0.08 (Hair, Black, Babin, Anderson, & Tatham, 2006).

5.2. Testing of hypotheses

To test the hypotheses relationships in the proposed model, the structural equation model was used. Specifically, six relations were tested, i.e. the strength and significance of direct effect of six independent variables on behavioral intention were determined. From a total of 6 tested relationships, 4 were statistically significant (Table 5). Of the two variables that reflect usability aspect (usefulness and ease of use), only usefulness has a significant effect on behavioral intention (estimate = 0.082, $p < 0.1$). Thereby, hypothesis H1 is supported. On the other hand, hypothesis H2 is rejected due to the fact that there was no statistically significant effect of the ease of use on behavioral intention in the model (estimate = 0.022, $p > 0.1$). The results show that respondents are willing to continue using the m-commerce service due to the utility that mobile payment provides, but not due to the simplicity of transactions.

Trust has proven to be a significant predictor of behavioral intentions (estimate = 0.151, $p < 0.01$). Payment via mobile phone has not yet become regular practice in some countries, such as the Republic of Serbia, which is why the aspect of customer trust in these services is very important for their frequent use in the future. Thereby, hypothesis H3 is supported. Unexpectedly, there has not been confirmed significant effect of mobility on behavioral intention in the study (estimate = 0.038, $p > 0.1$). Therefore, hypothesis H4 is rejected.

Two variables that have the strongest influence on behavioral intention in the proposed model are customization (estimate = 0.326, $p < 0.01$) and customer involvement (estimate = 0.299, $p < 0.01$). It is obvious that consumers, who are willing to engage in the process of creating new services and whose personal values, needs and lifestyles are consistent with the concept of mobile commerce and mobile payment, show a high degree of readiness for the recommendation and continued use of these services in the future. In fact, in order to use mobile services in some future period, it is important that consumers become familiar with them and that this manner of doing business becomes an integral part of their self image. This supported hypotheses H5 and H6. M-commerce is one of the new services, mostly used by younger people who frequently use the Internet and modern information-communication technologies. They usually accept m-commerce as an integral part of their lifestyle and they are willing, with their ideas, to help the improvement of these services. They are usually familiar and skilled in the use of mobile devices and services, so they find it easy to use m-commerce. Also, as frequent users of mobile devices, they find the aspect of mobility as something normal and expected, which all is in favor of the rejection of hypothesis H2 and H4. It is also important to point out that the independent variables explain 68.6% of variance in behavioral intention ($R^2 = 0.686$).

5.3. Neural network analysis

This study employs a multi-analytical approach by combining SEM and neural network analysis, one of the most important artificial intelligence techniques. Conventional linear statistical techniques, such as SEM and Multiple Regression Analysis (MRA), are able to detect only linear relationships, which may lead to over-simplification of complex decision-making processes (Chan & Chong, 2012; Sim, Tan, Wong, Ooi, & Hew, 2014; Tan, Ooi, Leong, & Lin, 2014). To overcome this problem, the application of the artificial neural network model, which may identify non-linear relationships, is suggested. The advantage of using this approach

Table 5
Hypothesized relationships.

Hypotheses	Estimates	C.R.	Sig.	Standardized estimates
H1: Usefulness → Behavioral intention	0.082	1.681	*	0.105
H2: Ease of use → Behavioral intention	0.022	0.250	n.s.	0.020
H3: Trust → Behavioral intention	0.151	2.767	**	0.179
H4: Mobility → Behavioral intention	0.038	0.408	n.s.	0.032
H5: Customization → Behavioral intention	0.326	3.161	**	0.318
H6: Customer involvement → Behavioral intention	0.299	3.940	**	0.354

Note: ** 0. 01 of significance; * 0. 1 of significance; n.s. – not significant.

is that the neural network model is able to learn complex linear and non-linear relations between predictors and the adoption decision (Chan & Chong, 2012). Also, ANNs are more robust and can provide higher prediction accuracy than linear models (Tan, Ooi, Leong et al., 2014) and may out-perform traditional statistical techniques, such as MRA (Chong, 2013a; Sim et al., 2014). On the other hand, due to its "black-box" nature, neural networks are unsuitable for hypothesis testing and examining causal relationships (Chan & Chong, 2012). Therefore, in this study, similar to Chong (2013b), Leong et al. (2013) and Tan, Ooi, Leong et al. (2014), a two-stage approach is adopted: first, SEM is used to test the overall research model and determine significant hypothesized predictors, which are then, in a second stage, used as inputs to the neural network model used to determine the relative importance of each predictor variable.

Artificial neural network (ANN) is, as defined by Haykin (2001), "a massively parallel distributed processor made up of simple processing units, which have a neural propensity for storing experimental knowledge and making it available for use". These simple processing units, called neurons or nodes, are analogous to the biological neurons in the brain. Other similarities to human brain are that knowledge is acquired by ANN through the learning process and it is stored in interneuron connection strengths called synaptic weights (SPSS, 2012).

There are many types of neural networks, but in this study we will use one of the most common and popular – feedforward back-propagation multilayer perceptron (MLP) (Chong, Liu, Luo, & Ooi, 2015; Huang, 2010; Negnevitsky, 2011). A typical neutral network consists of several hierarchical layers, i.e. one input, one or more hidden and one output layer. The number of hidden layers depends of the complexity of the problem to be solved. With one hidden layer, any continuous function can be represented, while with two hidden layers even discontinuous functions can be modelled (Negnevitsky, 2011). In the technology acceptance neural network models usually only one hidden layer is used (Chong et al., 2015; Chong, 2013a; Chong, 2013b; Huang, 2010; Leong, Hew, Tan, & Ooi, 2013; Sim et al., 2014; Tan, Ooi, Leong et al. (2014)). Each layer consists of neurons, which are connected with the neurons of the following layer and each connection is represented by an adaptable synaptic weight. In the feed-forward networks the signals are fed forward from the input layer, through the network, to the output layer. MLP belongs to the class of supervised learning ANNs, which means that knowledge is stored in the network by iteratively exposing it to patterns of known inputs and outputs. The error, i.e. the difference between desired (known) and actual (predicted) output, is calculated and propagated back in the opposite direction, in order to adjust synaptic weights so to minimize the estimation error.

The number of neurons in the input layer is equal to the number of inputs, i.e. predictors, while the number of neurons in the output layer is equal to the number of outputs, i.e. dependent variables. The number of neurons in the hidden layer affects both prediction accuracy and speed of network training. Simulation experiments indicate that to some point higher number of neurons in the hidden layer gives higher estimation accuracy (Negnevitsky 2011); however, too many of them can dramatically increase the computational load. Another problem is over-fitting. If the number of hidden neurons is too big, the network might simply memorize all training examples and not be able to generalize, i.e. to give correct output with data not used in the training. There is no heuristic way to determine the number of hidden neurons, so usually the trial-and-error (Chan and Chong, 2012; Chong et al., 2015; Chong, 2013a, 2013b) and the rules-of-thumb are used. One of the most widely known empirically-driven rules-of-thumb is that the optimal number of hidden neurons is usually between the number of the input and number of the output neurons (Blum, 1992). Many researchers suggested other rules, in which the number of hidden neurons also depends on the number of both input and output neurons (Gnana Sheela & Deepa, 2013). For example, Shibata and Ikeda (2009), Yao, Tan, and Poh (1999) and Panahian (2011) suggested that the number of hidden neurons m could be calculated as follows:

$$m = \sqrt{n \cdot l}$$

where n – is the number of input neurons and l – is the number of output neurons.

On the other hand, Trenn (2008) suggested the following equations for the calculation of the number of hidden neurons m:

$$m = \frac{n + l - 1}{2}$$

Some researchers have already proposed even simpler, yet effective rules, depending only on the number of the input neurons, like Yao et al. (1999) and Panahian (2011), who suggested logarithmic dependence:

$$m = \ln(n)$$

or Fang and Ma (2009), rather similarly stating:

$$m = \log_2(n)$$

Despite its importance, there is no unique rule for selecting the optimum number of hidden neurons. It should be noted that, in certain cases, all these rules-of-thumb should be tested before the final application. In most cases, the network that performs best on the testing set with the least number of hidden neurons should be selected. Also, there are many other factors that can influence selection of the number of hidden neurons, like the number of hidden layers, the sample size, the neural network architecture, the complexity of the activation function, the training algorithm, etc. (Gnana Sheela & Deepa, 2013).

In our research, neural network is modelled in SPSS 20, with the input layer consisting of four independent significant variables from SEM (i.e. trust, perceived usefulness, customization and customer involvement), while the output layer consists of one output variable (behavioral intention). Following the recommendations given above, the number of nodes in one hidden layer is set to 2. Sigmoid function is used as an activation function for neurons in both hidden and output layers (Chan & Chong, 2012; Leong et al., 2013). In order to increase the effectiveness of training, i.e. to provide shorter training times and better performance (Negnevitsky, 2011), all inputs and outputs were normalized to the range [0,1].

In order to avoid over-fitting, a ten-fold cross validation was performed, whereby 90% of the data was used for network training and the remaining 10% was used for testing, i.e. to measure the prediction accuracy of the trained network (Chong et al., 2015; Chong, 2013a; Chong, 2013b; Leong et al., 2013; Sim et al., 2014; Tan, Ooi, Leong et al., 2014). As a measure of the predictive accuracy of the model, the Root Mean Square of Error (RMSE) of both training and testing data sets for all ten neural networks, as well as the averages and standard deviations for both data sets are computed and presented in Table 6.

The average RMSE of the neural network model are quite small (0.1013 for training data and 0.0973 for testing data), indicating a quite accurate prediction (Leong et al., 2013; Sim et al., 2014; Tan, Ooi, Leong et al., 2014).

The importance of every independent variable is a measure of how much the value predicted by the network model varies with different values of the independent variable (Chong, 2013a). The normalized importance is the ratio of the importance of each predictor to the highest importance value. The results of the sensitivity analysis are presented in Table 7.

Table 6
RMSE values for the neural networks.

Neural network	Training	Testing
ANN1	0.1015	0.0991
ANN2	0.1021	0.0885
ANN3	0.1009	0.0918
ANN4	0.1039	0.0789
ANN5	0.1006	0.0982
ANN6	0.0976	0.1210
ANN7	0.1019	0.0954
ANN8	0.1030	0.0888
ANN9	0.1000	0.1158
ANN10	0.1015	0.0951
Average	0.1013	0.0973
Standard deviation	0.0017	0.0126

Table 7
Normalized variable importance.

Predictors	Normalized importance
Customization	1,000
Involvement	0,687
Trust	0,425
Usefulness	0,288

Based on the presented neural network analysis, customization is the most significant predictor of m-commerce acceptance, followed by customer involvement, trust and usefulness.

6. Conclusion and implications

6.1. Summary of the study

The study presents and tests a new model that contains six potential predictors of behavioral intention (usefulness, ease of use, trust, mobility, customization and customer involvement). The model contains a specific structure of independent variables, since there are other dimensions in it that may contribute to a more frequent use of mobile services in the near future, except for the variables that reflect usability (usefulness and ease of use). In this context, the model emphasizes the importance of customization, customer involvement and trust for creating behavioral intentions. We may emphasize, as the main result of the study, the fact that the development of long-term relationships with customers in the field of mobile business primarily depends on the ability of mobile operators to adapt their services to the needs, personal values, and lifestyle of their customers and to develop in them readiness for active participation in the improvement of existing services and the creation of new ones.

An innovative methodology that is based on the combined application of structural equation modeling and neural networks provides special originality to the paper. In this sense, after checking the validity of the model and testing the effect of independent variables on the dependent variable within the SEM analysis, neural networks were used in the research as well, thus enabling additional verification of the results provided by the SEM analysis. The paper provides useful theoretical implications to academic researchers and scholars, as well as managerial implications to mobile service operators.

6.2. Theoretical implications

Two dimensions of usability were used as potential antecedents of behavioral intention. It is interesting to point out that only the effect of usefulness on behavioral intention proved to be statistically significant. A similar result was confirmed in studies conducted by Kim et al. (2010), Liebana-Cabanillas et al. (2014b), Wei et al. (2009), Wu and Wang (2005), and Zarmpou et al. (2012). On the other hand, no significant effect of ease of use on behavioral intention was confirmed in our study. Although at first glance the result seems surprising, similar findings were obtained in studies conducted by Chong et al. (2012), Wu and Wang (2005), Zarmpou et al. (2012) and Wei et al. (2009). It is obvious that respondents consider the dimension of usefulness of mobile services to be very important for their future use. However, since it is a relatively new kind of service that is still predominantly used by younger consumers, many consumers have become familiar with how to use it. For them, the implementation of mobile transactions is a simple process, which reduces the significance of the variable ease of use for the future use of this service.

In the conceptualized research model, trust is noted as a statistically significant driver of behavioral intention. The aspect of trust is very important, especially when it comes to the use of new services or services that require high financial value. The realization of transactions via mobile phones in the Republic of Serbia is a service expected to increase in the future. For now, some people – especially older ones – are still suspicious of the use of these services. In this respect, users' trust in the security and accuracy of the payment and of all the data plays an important role in developing a long-term relationship with mobile operators. A significant influence of trust on behavioral intention was confirmed in previous studies as well (Chong et al., 2012; Lin and Wang, 2006; Zhang et al., 2012).

It is worth pointing out a research finding that indicates that mobility does not have a statistically significant effect on behavioral intention. One of the primary benefits of using mobile devices for commercial activities is exactly the mobility that enables users to make transactions at any time and from anywhere. An insignificant effect of this variable on behavioral intention can be justified by the fact that the consumers of mobile services are mainly younger citizens who frequently access the Internet on their mobile phones, so getting informed, socializing and performing many other activities on the Internet has become an integral part of their lives. Therefore, the mobility is a component of their lifestyle, which reduces the importance of this variable for the development of behavioral intention. For these respondents, mobility is simply not the factor that leads to future use, but something that is understood as normal and common in the lives of new consumers.

Two variables that have distinguished themselves as the strongest predictors of behavioral intention are customization and customer involvement. For the use of mobile commerce systems in the future and for their recommendation, it is very important that the lifestyle, personal values and needs of consumers are in line with their characteristics and advantages. Positive behavioral reactions can be expected from those consumers who are willing to give ideas to employees regarding the improvement of existing services and the creation of new ones. It is precisely the significance of these two variables that suggests that, for now, mobile services are mainly used by those consumers who are familiar with the use of information technologies, which is why mobility and ease of use are less significant.

6.3. Managerial implications

The results of the conducted study can be very useful for the management of mobile companies and m-commerce providers in their efforts to build a stable base of loyal customers. Since the use of mobile services is still relatively new, it is essential that the government, as well as mobile service providers, create appropriate educational and marketing campaigns that show citizens the benefits of this system of trade. It is particularly worth pointing out the importance of using m-commerce systems for improving business activities and operating performances.

Since customization and customer involvement were singled out as two key drivers of behavioral intention, it is important that customers are well trained for the use of mobile services, in order to eventually become familiar with a given system of transaction implementation. In this regard, the employees of mobile providers could provide personal services to customers in terms of acquiring skills for the use of these systems. In addition, the brochures which give a detailed overview of all the benefits and the process of implementation of mobile transactions can be distributed to customers in the premises of mobile operators. If m-commerce providers train consumers effectively in the use of these services and show them all their benefits through quality educational campaigns, they will attract new consumers through positive word-of-mouth. It is very important to promote the usage of mobile commerce systems as an integral part of new consumers' lifestyle. Also, it is necessary to allow customers to adapt m-commerce applications to their needs and habits. It is also desirable that customers get involved as much as possible in the development of new applications and services. When it comes to creating long-term profitability in modern-day business, it is not enough that companies create products with excellent technical specs (technology push strategy) if these products were not previously aligned with the needs and desires of consumers. An essential initial taks for management is that they should research consumers' attitudes and to develop new products/services in accordance with their requirements and needs (demand-pull strategy). In this sense, the consumer research provides useful information as a basis for the successful management of the company's research, development and production activities. It is therefore rather important that the users with their ideas and suggestions actively cooperate with the managers in the process of creating new products and services.

The emphasis should be on strengthening citizens' trust in the security of these types of services. In this context, it is important that citizens are well informed about the data protection system. Moreover, it is preferable that employees focus on the comparative advantages of mobile commerce as opposed to its alternatives. It is also necessary to offer consumers a solid refund guarantee in case of possible mistakes when implementing transactions.

It is also worth noting the importance of efficient and secure information and data management. M-commerce often includes transfer of sensitive personal and financial data which is performed wirelessly and could be easily intercepted and misused. So, in order to preserve data integrity and privacy and further increase consumer trust, advanced data management techniques such as data encryption, should be implemented. Also, taking into account the importance of customization, and therefore the necessity to offer consumers the option to customize their experience, products and/or services, m-commerce providers must implement efficient management of user accounts, profiles and settings.

7. Limitations and future research

The conducted study has several limitations. Firstly, the study was conducted at one time point. In future research, it is advisable to conduct research in successive time intervals, which would enable to observe changes in consumer attitudes. This is particularly important in the case of the analysis of new services, such as mobile commerce systems. Secondly, the research was conducted only in the territory of one country. Therefore, it would be useful to conduct cross-cultural study as well, to compare the preferences of different nations. Thirdly, it would be preferable to carry out a comparison of environments of different demographic groups, especially when it comes to age as a criterion for dividing survey respondents. It would be interesting to compare the results obtained in different age groups and see which statements lead to statistically significant differences. Fourthly, future models could also include some additional variables. With the exception of trust, it is important to include new variables that reflect the security dimension, such as perceived security and perceived risk. In addition, social influence could play a moderator role in the new models, to determine whether this variable changes the strength of correlation between independent variables and behavioral intention.

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Appendix A.

Construct	Items	References
Perceived usefulness	Using m-commerce improves my work performance. Using m-commerce improves my productivity. Using m-commerce enhances my effectiveness in my work.	Chan and Chong (2013)
Perceived ease of use	It's easy to use m-commerce. M-commerce is understandable and clear. Using m-commerce requires minimum effort. Learning to use m-commerce is easy.	Chong et al. (2012), Wu and Wang (2005), Wei et al. (2009)
Trust	Transactions via m-commerce are safe. Privacy of m-commerce users is well protected. M-commerce transactions are reliable. Security measures in m-commerce are adequate.	Chong et al. (2012), Zarmpou et al. (2012)
Mobility	M-commerce can be used anytime M-commerce can be used anywhere M-commerce can be used while traveling Using m-commerce is convenient because my phone is almost always at hand	Kim et al. (2010)
Customization	I think using m-commerce meets my needs. M-commerce offers information and services in line with my preferences Using m-commerce is in line with my personal standards and values	Yeh and Li (2009)
Customer involvement	If I have a useful idea on how to improve m-commerce, I let the provider know. When I experience a problem using m-commerce, I let the provider know about it. I would like to be included in development of new m-commerce products and services.	Yi and Gong (2013), Svendsen et al. (2011)
Behavioral intention	I intend to use m-commerce in the near future. I believe my interest in m-commerce will increase in the future. I will recommend others to use m-commerce. I will encourage my friends and relatives to use m-commerce.	Zarmpou et al. (2012), Gaur, Xu, Quazi, and Nandi (2010)

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